The missing risks of climate change

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ABSTRACT

The risks of climate change are enormous, threatening the lives and livelihoods of millions to billions. The economic consequences of many of the complex risks associated with climate change cannot, however, currently be quantified. We argue that these unquantified, poorly understood, and often deeply uncertain risks can and should be included in economic evaluations and decision-making processes. We present an overview of these unquantified risks and an ontology of them founded on the reasons behind their lack of robust evaluation. These consist of risks missing due to (a) delays in sharing knowledge and expertise across disciplines, (b) spatial and temporal variations of climate impacts, (c) feedbacks and interactions between risks, (d) deep uncertainty in our knowledge, and (e) currently unidentified risks. We highlight collaboration needs within and between the natural and social science communities to address these gaps. We also provide an approach for integrating assessments or speculations of these risks in a way which accounts for interdependencies, avoids double counting and makes assumptions clear. Multiple paths exist for engaging with these missing risks, with both model-based quantification and non-model-based qualitative assessments playing crucial roles.

1 Introduction

There is overwhelming evidence that the risks and impacts from rising concentrations of greenhouse gases in the atmosphere are very significant, will impact nearly every aspect of human life and the environment, and could ultimately prove to be devastating. An apparent incongruity exists between the pervasiveness of anticipated physical changes and the relatively modest total losses often estimated in economic evaluations[1,2]. Part of the explanation for this mismatch comes from "missing risks": the risks that are not currently included in economic evaluations because of their uncertainty, our limited understanding of them, or because existing economic models do not capture them in sufficient detail.

The interplay within and between different physical and social systems plays a crucial role in defining when and where impacts will manifest themselves and these interactions are often only poorly understood. This leads to large and growing uncertainty estimates and a wide range of incompletely understood and underestimated risks[3]. For example, the potential for climate change impacts to drive social discontent, dislocation and relocation, and instability and conflict, are all deeply uncertain, but potentially crippling.

Excluding these risks from economic assessments is equivalent to placing a probability of zero upon their occurrence. This, clearly, is not the case. Similarly, the common practice of engaging only with the expected levels of impacts and reporting central confidence bounds can undermine the ability of decision-makers to engage with the actual range of risks. The overall consequence is an underestimation of the total risks of climate change. This paper aims to identify, classify, and suggest ways to engage with some of the most significant risks that are not currently captured by socioeconomic evaluations of climate change, from both a natural and social perspective. As an example of how this can be achieved we present a demonstration of how diverse impact estimates or assumptions can be coherently combined.

2 Background

Economic evaluations of the risks of climate change are a crucial input into policy-making and long-term planning processes for businesses and communities. Various studies have projected the costs of climate impacts (damages) across multiple sectors[4,5], while Integrated Assessment Models (IAMs)[1] produce global estimates of the social cost of carbon (SCC)[6]. Such assessments generally

[1] Throughout the paper, we use the term IAM to refer to both Benefit-Cost IAMs (BC-IAMs), as the tools incorporating damages as standard, and Detailed Process IAMs (DP-IAMs), which traditionally focus on cost-

intend to go far beyond financial risks and involve "non-market" effects, such as losses to ecosystems and broader human well-being.

The aim in quantifying climate risks is usually to produce probability distributions for possible impacts in quantities such as meters of sea-level rise, decreased biodiversity indices, people affected by certain types of event, or percent losses to GDP. Anthropogenic climate change, however, takes the climate/social system into a regime never before experienced, and consequently robust, reliable probabilities are rarely a possibility[7–9]. Nevertheless, even scientifically founded rough estimates of such distributions are valuable for illuminating the characteristics of the integrated complexities of the economic impacts of climate change. Indeed, even where no credible quantifications exist we might still be able to set plausible limits.

The distributions of climate change impacts produced by economic models are often taken as probability distributions, but in practice they suffer from deep uncertainties[7,10]. Consequently, while models play a part in supporting policy, model outputs are insufficient to facilitate effective engagement with many risks and it is important to consider risks associated with climate change even when no quantifications exist or deep uncertainties abound.

The full range of risks from climate change is currently missing from economic evaluations. There are two broad reasons for this. First, a considerable time delay exists between understanding of physical risks, economic understanding of the implications of those risks and their nonlinear social feedbacks, and incorporation of this understanding into economic models and analyses. Second, high levels of uncertainty and incomplete understanding of physical processes can drive scientists to be conservative in reporting them, or drive them to focus on central estimates.

It is helpful to distinguish five kinds of uncertainty which factor into economic impact uncertainty (box 1, visualized in Figure 1). The first derives from uncertainty about future socioeconomic policy scenarios (UC1). This scenario uncertainty will not be an important part of our discussion because we are concerned with informing policy choices which generally involves a comparison of different socioeconomic and policy scenarios. The second kind refers to the parameters which describe the processes of the climate and social systems (UC2), such as climate sensitivity, elasticity of marginal utility of consumption, rate of ice loss from the Greenland and

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effectiveness analysis of mitigation strategies, but are increasingly developed to integrate impact estimates.

Antarctic ice sheets, the potential increased mortality related to heat etc. Model uncertainty (UC3) arises from differences in how the structure of the problem is approached by different experts and modeling centers and the choice of computational and statistical parameters available for tuning. Even small differences in models could produce large differences in outcomes over time[11] (a proposed Hawkmoth effect analogous to the Butterfly effect).

[Box 1 about here.]

Trajectory uncertainty (UC4) describes the intrinsic, aleatoric, uncertainty in what the future trajectory will actually be. In deterministic models such as GCMs, it arises from their nonlinear dynamical behavior and is referred to as "initial condition uncertainty"[7]. Although IAMs typically do not have this form of chaotic variability, the socioeconomic system they represent is similarly nonlinear and variable, and trajectory uncertainty can be explored within them using stochastic representations[12–14].

Finally, model inadequacy (UC5) refers to the known and unknown limitations in our models: their incomplete representation of processes which could significantly influence the outcome in the real world system they are designed to represent. Acknowledging model assumptions and inadequacies is particularly important where quantitative models are aimed at informing policy decisions, and increasing model coverage and complexity often will not increase its relevance and accuracy[15].

While epistemologically distinct, parameter, model, and trajectory uncertainty (UC 2-4) can be combined in impact evaluations, since they are functionally similar for decision-makers. Scientists, however, engage with them quite differently. Of these, parameter uncertainty is the most susceptible to reduction through data collection and empirical studies, although this can be a slow process. Scientific progress may increase or decrease model uncertainty. The sensitivity behind trajectory uncertainty derives from both the finest details of the starting conditions[16] and their large scale, generic features[17]. The former is irreducible but the latter is, at least potentially, reducible through further research and better observations[7]. We argue that risk evaluations should incorporate UC 2-4, alongside descriptions of model limitations (UC5) to describe our combined uncertainty around final outcomes.

[Figure 1 about here.]

Decision-makers are often adept at handling uncertainty and could use information on both low-probability/high-damage outcomes and unknown-probability/high-damage outcomes. Consider, for instance, the sixth IPCC report which allows for up to 10% probability that climate sensitivity is outside the 2-5 degree range, with much of this probability reflecting the deep uncertainty in the upper tail of the probability distribution[18,19]. The associated risk of high levels of warming is significantly higher than acceptable risk levels in public health (e.g. 1 in 10,000[20]) and indeed uncertainty in the tail probabilities have been shown to have orders of magnitude impact on economic assessments of future welfare and therefore on the value of emissions reductions[21]. Even the possibility of a runaway greenhouse effect due to anthropogenic climate change cannot be entirely ruled out[22]. Typically decision-making has multiple objectives, and harmful, low-probability outcomes can play a significant role. It is therefore important for decision-makers to be aware of harmful processes, even if their likelihood is unknown. For example, there is little basis for knowing whether climate impacts on GDP growth rates[23] will continue into the future, but if they do, the result would be devastating. Furthermore, risks are sometimes excluded when they are not fully understood or where there is considerable variation in estimates (e.g., health risks[24]). If only those risks considered "likely" (above 66% probability) in the IPCC reports are accounted for, a large portion of potential impacts would be erroneously given a 0% probability. Some of these risks are incredibly complex, with impacts cascading across multiple sectors and involving considerable path-dependence (e.g. biodiversity or ecosystem losses). Most are fraught with "deep uncertainty", with scientists disagreeing on the basis for providing reliable estimates (e.g. the potential for climate-driven conflict[25]). These challenges are not, however, insurmountable barriers to their inclusion in policy-making or economic valuations. There are opportunities to use imprecise probabilities, formal possibilistic approaches and informal possibilistic approaches[26] such as "Tales of the Future", which encapsulate physically realistic and plausible futures focused on the aspects of the system of concern[27,28].

3 Ontology of missing risks

Here we distinguish between five categories of currently missing risks and suggest potential solutions on how to start integrating them into current and future studies. The categories below are based on the reasons behind their exclusions, and these reasons provide insight into how they can be engaged with in the near future.

3.1 Missing biophysical impacts

One group of missing risks arises from the calibration of the IAMs, which are often decades out of date[29]. This is true of several risks now considered to have high probability at current and future levels of warming, such as the collapse of the AMOC by 2300 (assessed as likely as not)[30] and abrupt permafrost melt by 2100 (assessed as high probability)[31], also see SI figure 1**.** The pathway from improved understanding of a climate phenomenon to its valuation in economic models can be long. It often requires that the understanding of relevant climate drivers reaches a point where the science is available beyond the climate science community, for instance through media like IPCC reports. As part of this process biophysical modeling is often required to translate climate risks into physical impacts; economists need to develop an understanding of the response of social systems to the physical impact, and a welfare valuation of these responses; and the risk then needs to be incorporated into IAMs, computable general equilibrium models (CGE), or other comprehensive analyses. This requires close collaboration between multiple disciplines[32,33].

The physical impacts and population exposure for a large number of relevant risks have already been quantified (see SI table 1). In some cases, a translation from impacts into welfare or monetary damages is readily available and these can be readily incorporated into evaluations. In other cases, readily-available valuations are unavailable (e.g., biodiversity loss, natural disasters) or resilience and general equilibrium effects are first-order concerns (e.g, water stress, migration). In this case, considerable work is needed to translate biophysical risks into economic ones. Examples of recent developments that are not captured in economic assessments include exposure of populations to natural disasters[34,35], the latest process-based impact-model intercomparisons across multiple sectors[36], and new statistical models of health, productivity, agriculture, and energy[37]. These impact estimates represent substantial developments beyond existing representations of these risks in the IAMs[38,39].

There are several possible causes for this gap, including: the disagreements within the impact community over the scale of impacts; a culture in economics that does not encourage large-team collaboration; and to some extent limited funding available for economic model development. The process for including these risks in the near future must confront multiple challenges. Economic damage assessments need damage functions which reflect the widest possible range of credible responses: recent advances in empirical damage estimates[37] go in the right direction but face the challenges of both connecting short-term weather-related impacts to long-term climate ones, and incorporating the endogeneity of adaptation. One approach to this problem is being pioneered at the Climate Impact Lab, and tries to address both problems. To account for adaptation, they use observed variation in temperature sensitivity[40]. To support incorporating these results into economic models as functions of climate rather than weather, they estimate impacts under downscaled projected weather and then index these uncertain impacts to expected climate, which allows them to be emulated in models that do not have daily weather or disaggregated sectors[41]. Parallel work at the Potsdam Institute for Climate Impact Research (PIK) develops channel-specific damage functions using process-models for use in economic models (e.g., [42]). However, integration of this new work into economic analyses requires that issues of valuation, equilibrium adjustments, and double-counting are resolved, which requires an interdisciplinary approach[43].

The ability to incorporate many risks into economic evaluations is being undermined by difficulties in bridging the climate science, economics, and modeling cultures. Examples include climate tipping points, conflict and migration, and topics from climate justice. Natural scientists and economic modelers struggle to find a common language to discuss the possible consequences of climate change. Bridging these gaps requires the repeated, collaboration-focused convening of researchers engaged in all aspects of the problem.

3.2 Spatial and temporal extremes

The spatial and demographic variations in impacts has emerged as one of the central features of economic damages: poor and socio-economic vulnerable groups in many regions are the most exposed to risks[5,43]. IAMs often represent the world in highly aggregated terms, describing only global results (e.g., DICE) or across multi-national regions (e.g., PAGE, FUND and RICE) and for representative agents. Although these variations can be parameterized in damage functions[44] or elasticity parameters[45], doing so hides the underlying source and consequences of climate risk.

Temporal extremes are also likely to play a significant role. While impacts of climate change result from the long-term evolution of temperature changes and sea-level rise, many will manifest as extreme shocks: heat-waves, storms, droughts. While projections of many natural disasters are available[35,46], they are not represented in IAMs and reported metrics typically hide the role of variability[4]. See examples of risks arising from spatial and temporal extremes in SI D.

It is a conceptual challenge to integrate the small spatial and temporal scales relevant for extreme events or the effects on different income groups and related distributional effects into the integrated assessment models operating on large world regions and long timescales. Spatially detailed research requires simulations and data often only available for few countries. New research examining the complexity of systems and potential impacts of climate change responses at scales ranging from individual households to national policy and global governance can help in this regard.

Traditionally, the highly aggregated approach of Benefit-Cost IAMs has supported their use in identifying climate policies that maximize global welfare, by relying on intertemporal optimization. Economic assessments of scenarios, however, do not require optimization, and higher resolution economic risk assessments have been produced for the United States and Europe[33], the consequences of tipping points[47], and country-level scale information using empirical damage estimates[48]. Improvements in stochastic optimization techniques also provide a pathway to increasing resolution while studying optimal mitigation[49].

A way to better engage with these features is to improve how heterogeneity, variability, and uncertainty are approached generally. We propose that there is an emerging way forward for combining parameter, model, and trajectory uncertainty, while considering model inadequacy, at high spatial and temporal resolution. First, impact models should be driven by downscaled inputs available at a monthly or higher frequency, over multi-decadal periods. This captures the interaction between the dynamic uncertainty represented by both natural variability of the climate system and climate change. Parameter uncertainty within the impact models should be represented by probability distributions over parameter values, simulated using Monte Carlos across multiple downscaled GCMs and multiple impact models, ideally drawing from initial-condition ensembles.

It is in addition important to improve how uncertainty is communicated to policy-makers. When presenting model-based information we recommend separating variability from uncertainty i.e. the 1-in-100 chance outcome for an impact conditioned on a model, alongside how that number varies between models. Finally, model inadequacy needs to be stated clearly, and unmodeled risks represented (e.g., with ember plots).

3.3 Feedback risks and interactions

Feedback processes are ubiquitous within and among the climate, environment and economic systems. Critical and sometimes overlooked risks arise from the complex interplay of climate change and variability, demographic shifts, economic insecurity, and political processes (see SI E). Physical risks are not independent of each other and climate change can act as a catalyst and stressor that accelerates and exacerbates conditions leading to cascading effects in the climate system and societal tipping points (see figure 2 and SI F). Feedback processes are often the source of heavy tailed distributions and are therefore closely linked to black swan events (see 3.4). However these interactions are often missing from analyses and thus represent a source of missing risks.

The complexity of feedback systems has slowed the process of both understanding them and modeling them. Compound, sequential, concurrent extremes would lead to lower thresholds (for a single driver) for substantial impacts as well as deeper impacts when two drivers align[50]. The overall lack of representation for this type of secondary effect leads to an underestimation of risk.

There is a need for new assessment and risk management frameworks that better incorporate uncertainty and complex, cascading risks, including systems approaches built upon interacting sectors, actors, geophysical hazards, scenarios, and story-lines. Approaches that utilize agent-based modeling and CGEs are now being developed, but more effort is needed to understand their potential contribution in a climate change context..

An important class of feedback risks is tipping points[51]. Climate, ecological, and social tipping points are transitory states of a feedback process beyond which a new basin of attraction will drive further system change, resulting in a qualitatively different and self-reinforcing regime. A wide variety of tipping points have been incorporated into analyses for individual papers, but representing the full collection has been a challenge[47].

One barrier to research on tipping points and climatic extremes being incorporated into economic evaluations is that they are not well represented in GCMs, and their associated downscaled products. Social scientists look to natural scientists to provide probabilities, time evolutions, and gridded projections to support their work. This is not always possible. Ensuring that climate scientists provide results in a form that is both robustly justifiable and can be readily incorporated into economic analysis requires bringing together the two disciplines.

[Figure 2 about here.]

3.4 Deep uncertainty

Deep uncertainty describes processes for which robust probability distributions do not exist. For many impacts, one or more steps in the estimation of hazards, exposure, vulnerability, and welfare suffers from deep uncertainty, in terms of, for instance, the extent of their impacts and their spatio-temporal probability or frequency (see SI G). In some cases, the appropriate metrics for quantification are unclear. Yet, they can (and should) still be factored into risk assessment and planning.

One class of impacts suffering from deep uncertainty is black swan events, characterized by their extreme nature and long-lasting consequences[52]. Statistically, black swan events are outcomes from the tails of heavy-tailed distributions, which are common in natural and human systems[51,53–55]. These events are difficult to predict, because they are so far outside of what we normally observe and often arise from interlinked instabilities. Because they depend upon and trigger changes throughout their systems, each black swan event can dramatically alter exposure to risks and force the need for developing new decision contexts. As advancing climate change places new stresses on climate and social systems, outcomes beyond the extremes observed within the historical record are increasingly possible. The high frequency of previously-considered “highly improbable” events requires their consideration in climate change evaluations. Some examples include technological breakthroughs (unforeseen dramatic efficiency gains, consequences of the new green revolution, etc.); governance and geopolitical reorganization (conflict, trade blocs, etc.); new climate regimes (unforeseen ocean circulation or ecosystem changes, etc.); funding mechanisms (green development bank, subsidies to tip the balance toward renewables, etc.); and disease outbreaks (COVID-19, Ebola, etc.).

Some of these deep uncertainties and black swan events can be explored through scenarios. Scenarios as a combination of broad narratives and quantitative projections based on models have been employed in climate science in the past[56]. It is important that climate narratives represent sequential and concurrent events across multiple regions and sectors of the global economy. The currently used Shared Socio-economic Pathways (SSPs) cover a range of socioeconomic futures, but these scenarios do not necessarily capture disruptive deviations from the past[57]. To truly assess deep uncertainty, the diversity and robustness of scenarios needs to receive more attention[58]. Computational techniques like cross-impact balances can be used to systematically explore large numbers of scenarios and the coverage of scenarios space. Alternatively, the vulnerability of a (policy) strategy to disruptions can be studied. A number of projects have built upon a storyline approach[27,28,59–61]. New speculative storylines can begin an iterative process whereby global and regional modeling exercises and storyline refinements can offer new insights.

Note that assessments of model uncertainty in multi-model intercomparisons and perturbed physics/parameter studies can not provide robust probabilities due to the shared features across models, their limited exploration of possibilities, and the conceptual lack of any basis for defining the shape of "model space" across which probabilities must be built[7]. Nevertheless, the uncertainty derived from such ensembles represents a starting point for consideration of deep uncertainty. Example applications include model evaluation with historical data and developing multi-sector, multi-model projections[62–64].

A similar process of reflection on deep uncertainties should be initiated with IAMs (and other models capturing impacts) and the economic damage integration process in general. Although IAMs have been intercompared in the past, a concerted intercomparison project would have a much broader focus on consideration of the implications of what is missing or inadequately incorporated at present.

3.5 Unidentified risks

Finally, it is appropriate to recognize a further set of risks completely unidentified in the academic literature. The coupled global environmental-human system can be disrupted in many ways that are unexpected or have not been studied. We take for granted many of the ways that the environment currently supports human needs, and not all of these functions are known, much less their sensitivity to climate change. Populations may respond to changes in their environments in unpredictable ways, driving social movements that take on a life of their own.

Because these risks are fully unknown and unquantified, we cannot directly include them in valuations, but we can still factor unidentified risks into decision making. Approaches exist for doing so. First, we could consider a precautionary principle, arguing that we might want to maintain the state with which we have long historical experience, even in the absence of clearly-identified risks. The precautionary principle is already embedded in the Paris Agreement, and underlies the results of Detailed Process IAM models which identify cost-effective implementations of given mitigation scenarios[6]. We can understand the risks we face by comparing the future world to the range of conditions experienced across instrumental records (e.g., see figure 3)[65]. The precautionary principle would motivate pairing economic welfare calculations with planetary boundaries or other deviations from historical ranges[66].

Second, there are normative, ethical arguments to maintain the natural state of the planet, out of a rights-based demand to not subject people to undue risks, for example[67,68]. The argument is that economic systems should conform to the values held by their stakeholders and that comprehensive economic evaluations should therefore account for infringements upon the stated priorities of each community.

[Figure 3 about here.]

Third, there are results from complexity science that provide ways to monitor the fingerprints of risks, even if we do not know their nature[69]. These can provide early warning signals, and suggest improving resilience even without clear dangers in sight.

4 Moving forward

Improving our representation and understanding of the missing risks in economic assessments of climate change impacts is a long-term goal. It demands greater coordination between the climate, impact and economic scientific communities, better approaches forgrounding economic projections in data, systems understanding and the latest climate science, and better representations of complex, interacting, heterogeneous systems. The different classes of missing risks described above each require different approaches for moving forward. Furthermore, foundational work is needed to understand the basis for deriving robust, actionable information when combining different kinds of information sources to generate comprehensive assessments– we should avoid potentially misleading, model-sensitive data.

We can distinguish three overlapping stages in this broad agenda. With existing knowledge we can already offer a better picture of the total risks of climate change by engaging in detailed, integrative work. This stage depends upon collating existing knowledge, preparing better narratives, and interpreting results in the context of missing risks. The second stage consists of work to map out the spaces that current models miss and to analyze where there may be value in improving existing models or developing better non-model-based approaches. This stage involves improving scientific inputs into quantitative economic assessments, improving representations of uncertainty, and engaging in explorations of the potential behavior and model intercomparisons of IAMs with respect to impact modeling. Finally, there is a long-term agenda, which requires targeted funding to support intensive engagement across disciplines, new model approaches and new types of modeling experiments designed to robustly test the sensitivity of policy-relevant conclusions to the nonlinear consequences of the initial state, structural model error and stochastic behavior and assumptions.

Finally, some risks have been treated as insignificant because of the long time horizon before they will be experienced with a measurable effect. Welfare losses in the future are typically discounted (reduced) in cost-benefit calculations. We will not address discounting in this paper, but we offer a few comments. First, discounting is inherently an ethical decision, so decision-makers should be careful about applying common conventions from the academic economic literature and might benefit from greater awareness of the undiscounted stream of damages. Second, under the risk of negative economic growth, it may not be economically or socially sensible to discount the future (e.g., under Ramsey discounting[70]). Third, alternatives to standard discounting are available (e.g., [71]), but best practices are needed.

4.1 Rapidly quantifying missing risks

Considerable information is available on many of the risks discussed in section 3, but it is not integrated in a way that can lead to comprehensive quantification. Here, we propose an illustrative general approach for combining uncertain and qualitative information about an indefinite but growing collection of risks. The framework highlights the gaps in existing knowledge, and aims to rapidly lower the barrier to incorporating a large number of currently missing risks.

Conditional on a temperature change of ΔT, we posit that each risk i can be described by an imprecise and possibly subjective distribution of possible consequences or impacts, $x_i \sim f_i(\Delta T)$. For our purposes, we are agnostic about the quantification of x_i, so long as the metric is consistent across all risks: for example, they could be in terms of percent welfare-equivalent GDP lost or lives negatively affected over the course of each lifespan. Suppose that each distribution embodies all forms of uncertainty (UC 2-5).

We can distinguish two broad forms of interdependencies between individual risks. First, the drivers behind the forms of uncertainty can be shared, so that a high impact from one risk is correlated with a high impact from another. For example, damages due to droughts and wildfires both depend upon precipitation changes, and are likely to be correlated, even after accounting for temperature changes. However, this points to the other form of interdependence: double-counting. If the same area is at risk from both droughts and wildfires, damages from one may already be accounted for in the estimation of damages from the other.

We address these both using a copula approach, which simplifies the representation of these interdependencies, and is detailed in SI A. This simple framework decomposes the problem of understanding the total missing risks into a series of discrete and cumulative steps:

1. Identifying a common metric for measuring risks.
2. Estimating or otherwise generating a probability distribution representing losses from each risk.
3. Determining the correlation of uncertainty between pairs of risks.
4. Determining the degree of double-counting between pairs of risks.

Furthermore, additional risks can be incorporated without revisiting existing estimates, allowing the process of including more missing risks to occur in a distributed fashion. The estimates used for steps 2, 3, and 4 may be subjective and will certainly involve deep uncertainty but they allow us to better understand risks and their interactions under various assumptions.

As an illustrative application of this framework, we combine estimates for a range of risks from recent literature, including natural disasters, ecosystem impacts, conflict, migration, sea-level rise, heat and cold mortality, and economic growth impacts (see SI table 1). As a consistent metric across all risks, we describe the number of lives disrupted, in terms of the population in 2010, at various levels of warming. As such, the results presented here do not provide a complete path to incorporating these risks in economic assessments, since welfare losses are not quantified.

We show these risks and their combined effects in figure 4. The greatest risks, in terms of central estimates for populations affected, are multisector energy risks (46% at 2 °C, 85% at 4 °C) and relative conflict risk (32% at 2 °C, 75% at 4 °C). However, heatwaves, productivity, and water stress all have tail risks (95% quantile) of greater than a quarter of the global population being affected. These risks can also be combined into a smooth functional form, potentially applicable in IAM-style models (see figure 4b). If the common metric wereeconomic damages (e.g. loss of GDP), the results couldbe used in IAMs in the form of a damage function.

[Figure 4 about here.]

Here, we have only discussed the negative impacts incident upon populations, but there are entangled positive impacts as well. Some of these are direct, such as increases in economic growth in some sectors and lives saved by milder cold winters. In addition, adaptation and migration can significantly reduce the overall risks.

Understanding the risk of 2, 3, and 4 °C global mean surface temperature anomalies requires not just a reporting of the existing risks that models provide, but also the incorporation of new classes of risks as well as the potential for disruptive unknown risks that could dramatically alter the context of future societal systems and anthropogenic climate change risks. It is hoped that recognition of these “missing risks” will improve the overall level of accounting for consequences associated with climate change under crediblewarming scenarios.

Acknowledgements

D.A.S. acknowledges support from the Grantham Research Institute on Climate Change and the Environment at the London School of Economics, the ESRC Centre for Climate Change Economics and Policy (CCCEP; ref. ES/R009708/1), and the Natural Environment Research Council through Optimising the Design of Ensembles to Support Science and Society (ODESSS;

ref NE/V011790/1). F.P. acknowledges funding through the CHIPS project, part of AXIS, an ERA-NET initiated by JPI Climate, funded by FORMAS (Sweden), DLR/BMBF (Germany, grant no. 01LS1904A), AEI (Spain) and ANR (France) with co-funding by the European Union (grant no. 776608).

Data Availability

All data used here are publicly available at the sources cited in the Supplementary Information.

Author contribution statement

All authors contributed equally to the writing of the manuscript. J.R. prepared the visualizations.

Declaration of interests statement

The authors declare no competing interests.

Figure captions

Figure 1. Compounding uncertainty in climate risks estimation. The process for developing risk estimates depends upon several stages of analysis, with uncertainty compounding across stages. Distributions are shown for an illustrative projection of changes to death rates in New Delhi (using data from [40]). Uncertainty in emission scenarios and their associated baseline socioeconomics, contributes to uncertainty in climate changes, local hazards, impacts, and economic damages (including costs of adaptation). Since climate risks can then affect emissions (e.g., populations after death tolls), there are also feedbacks between these processes further increasing uncertainty.

Figure 2. Stylized channels by which risks can interact and compound. Arrows in red show channels of interaction. **Cascading tipping points** refers to the increased probability of one tipping point because of the triggering of another[72]. **Cascading disasters** can occur as natural disasters heighten the risk of other disasters (e.g., droughts causing wildfire). With **multiple stressors**, as climate stresses proliferate, the resilience and adaptive capacity of populations can be sapped[50]. As with the climate system, **cascading social changes** can emerge, such as migration increasing the risk of conflict[51]. As populations adapt and develop, this will produce **simultaneous exposure/sensitivity changes**, which may increase risks (e.g., if populations further concentrate on coasts or along rivers).

Figure 3. Hazards shifting outside of their historical range. (a) Hazard that most exceeds the distribution from recent (1980 - 2009) history, measured with a z-score from 9 GCMs

in WorldClim[73] in 2050 under SSP3-7.0, amongst high logged precipitation in the wettest month, low logged annual precipitation, coefficient of variation of precipitation, minimum temperature of the coldest month, maximum temperature of the warmest month. Significance is determined by bootstrapping the 95% confidence interval, and determined to be at a z-score of 0.98. (b) As above, showing the distribution across the global population of the z-scores.

Figure 4. Distributions of projected population at risk. (a) Each panel shows the distribution of the portion of the global population that could be impacted by a risk or a combination of risks. These represent some of the major missing risks discussed in the text. Each distribution is based on a single study, and the collection of missing risks is not comprehensive. The dashed lines represent the 99th percentile of the distributions. Specifics on how calculations are done and population impacts are determined are described in SI Bthe appendix. (b) Smooth spline representation of the combined population affected across all risks shown in panel (a). Spline is fit to each Monte Carlo drawn value at 2, 3, and 4 °C, and constrained to a value and slope of 0 and a GMST change of 0 °C and to be weakly monotonic after 4 °C. Shaded region shows the 1 - 99th percentile.

Boxes

Box 1: **Types of within-process uncertainty.**

Within each process modeled to estimate a risk, aggregate uncertainty derives from various types of uncertainty in the assumptions. These are summarized below.

Source of uncertainty	Common representation	Example
(UC1) Scenario uncertainty	Representative concentration pathways (RCPs), Shared Socioeconomic Pathways (SSPs), Shared Policy Assumptions (SPAs).	Business as usual vs. INDC commitments vs. transitions necessary to limit warming.
(UC2) Process parameter uncertainty	Probability density functions across process parameter values.	The equilibrium climate sensitivity (ECS) distribution used in an IAM.
(UC3) Model uncertainty	Results from multiple models or perturbed physics explorations.	Global climate model (GCM) multi-model and perturbed physics[74] ensembles, ISIMIP impact model[75] and process-based integrated assessment model[76] intercomparisons.
(UC4) Trajectory uncertainty	Multiple realizations from a model with perturbed initial conditions.	Multiple model runs produced with individual GCMs or nonlinear models.
(UC5) Model inadequacy[7] (Structural limitations of our models)	Descriptions of model limitations.	The lack of a stratosphere or aspects of atmospheric chemistry in GCM climate simulations. The lack of time/ temperature dependent climate sensitivity or types of climate impacts in IAMs.

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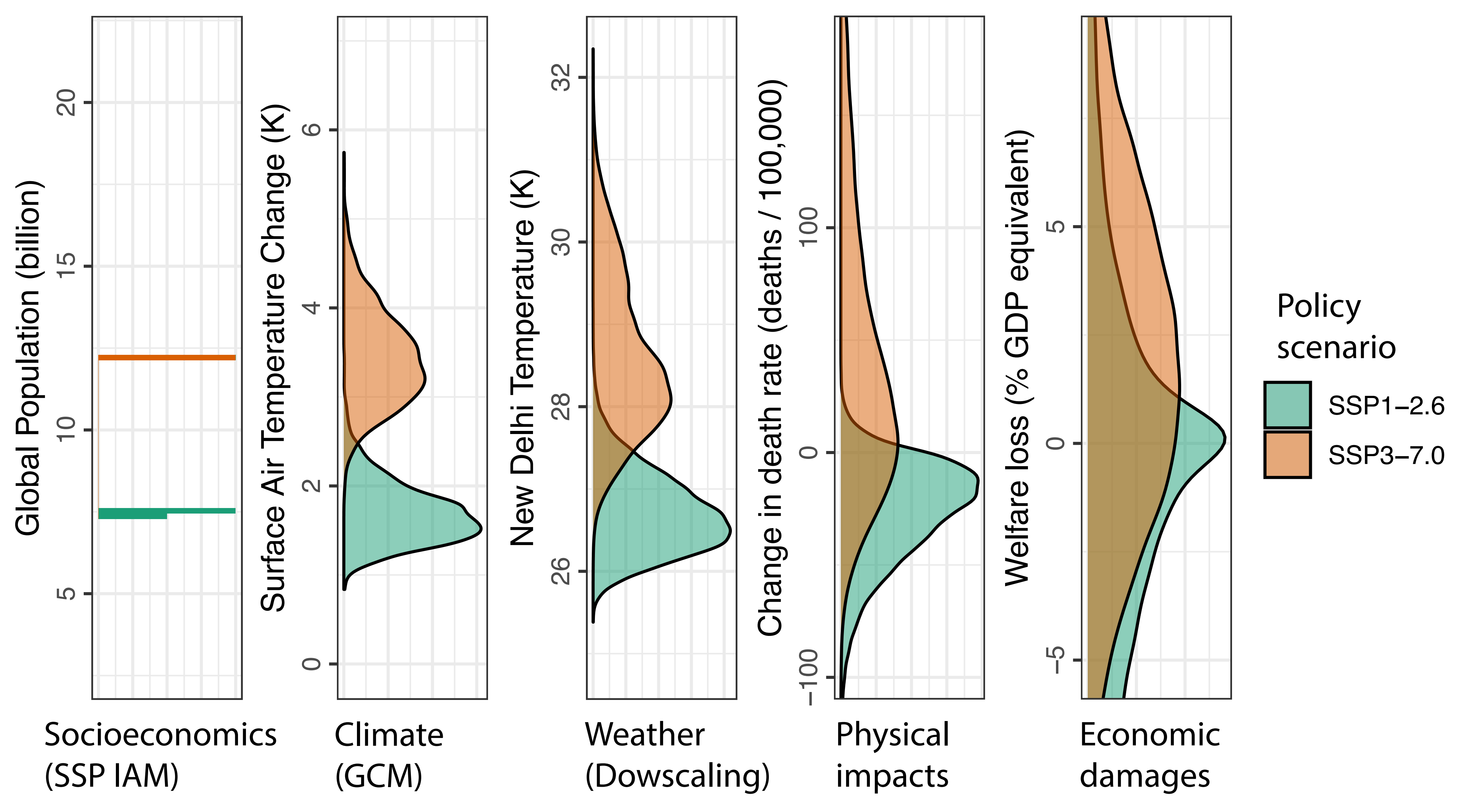
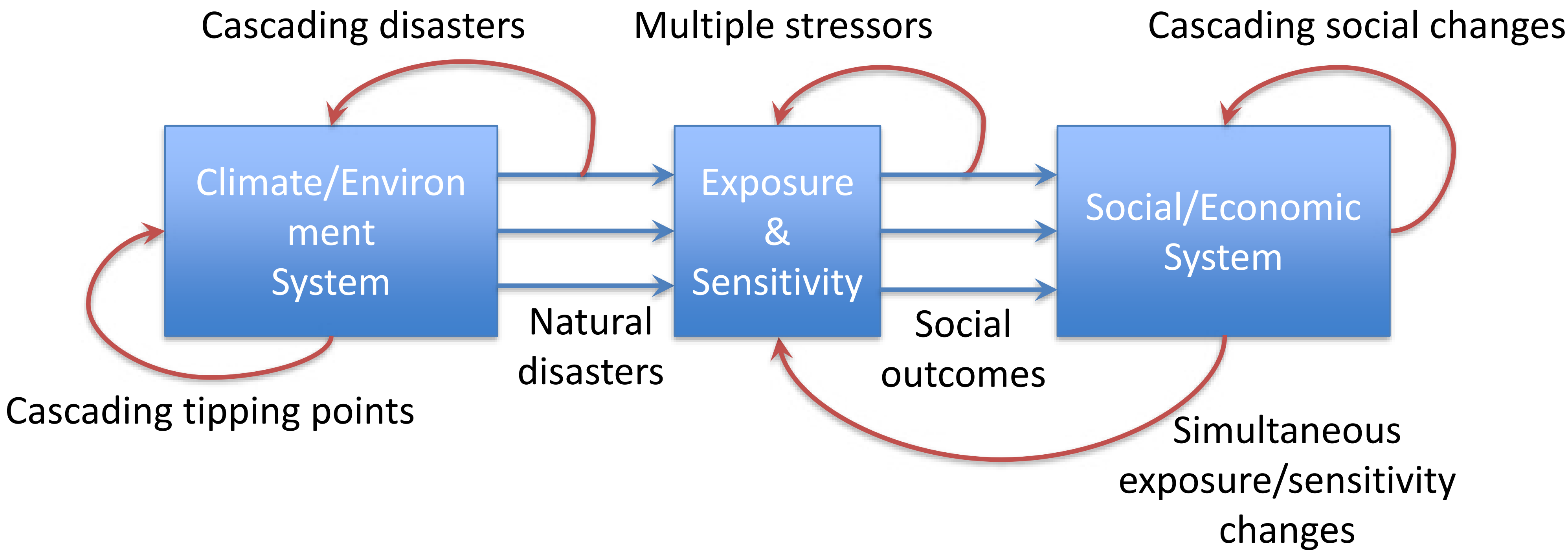
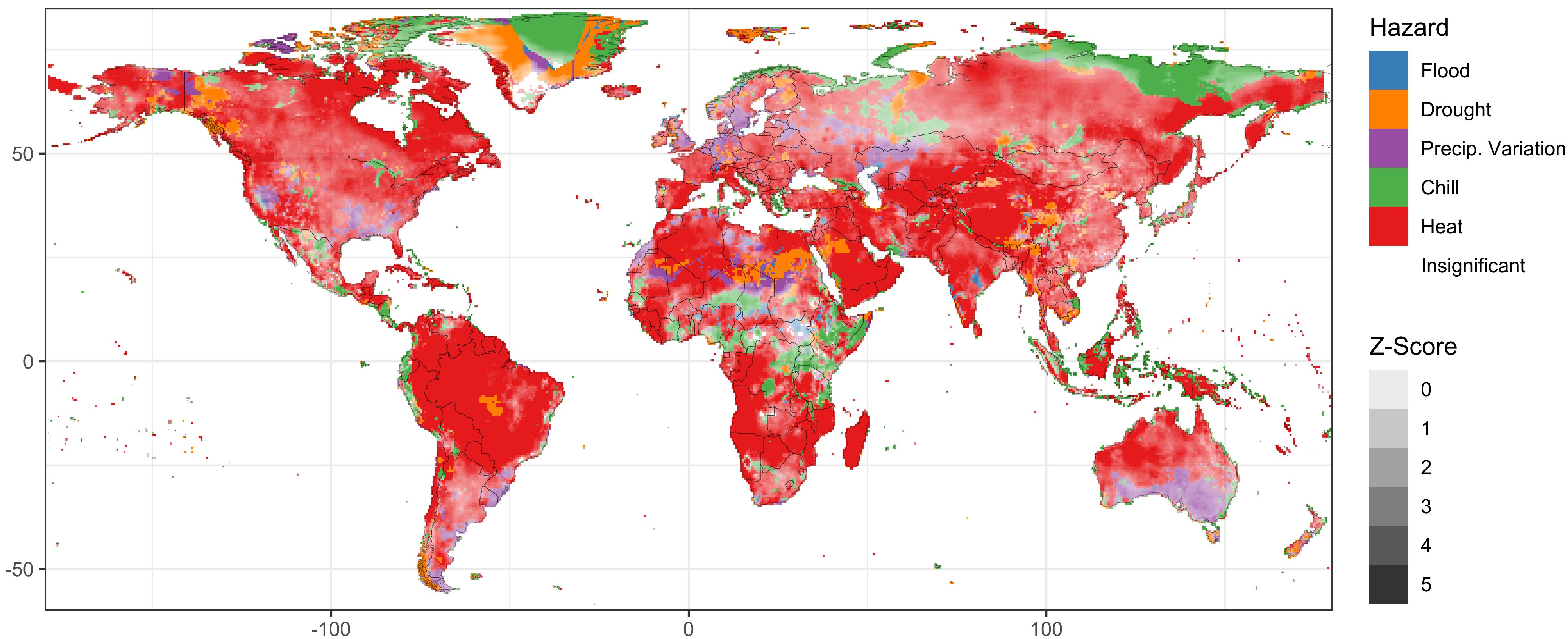
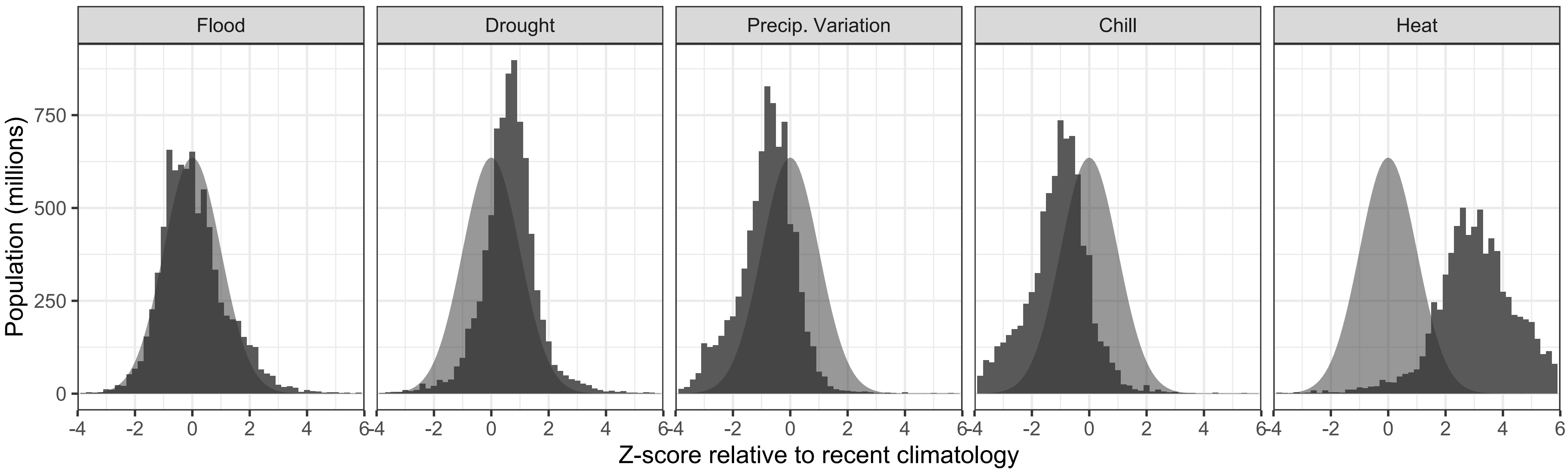


Global Population (billion)
5
10
15
20
Surface Air Temperature Change (K)
0
2
4
6
New Delhi Temperature (K)
26
28
30
32
Change in death rate (deaths / 100,000)
−100
0
100
Welfare loss (% GDP equivalent)
−5
0
5
Policy scenario
SSP1−2.6
SSP3−7.0
Socioeconomics (SSP IAM)
Climate (GCM)
Weather (Dowscaling)
Physical impacts
Economic damages

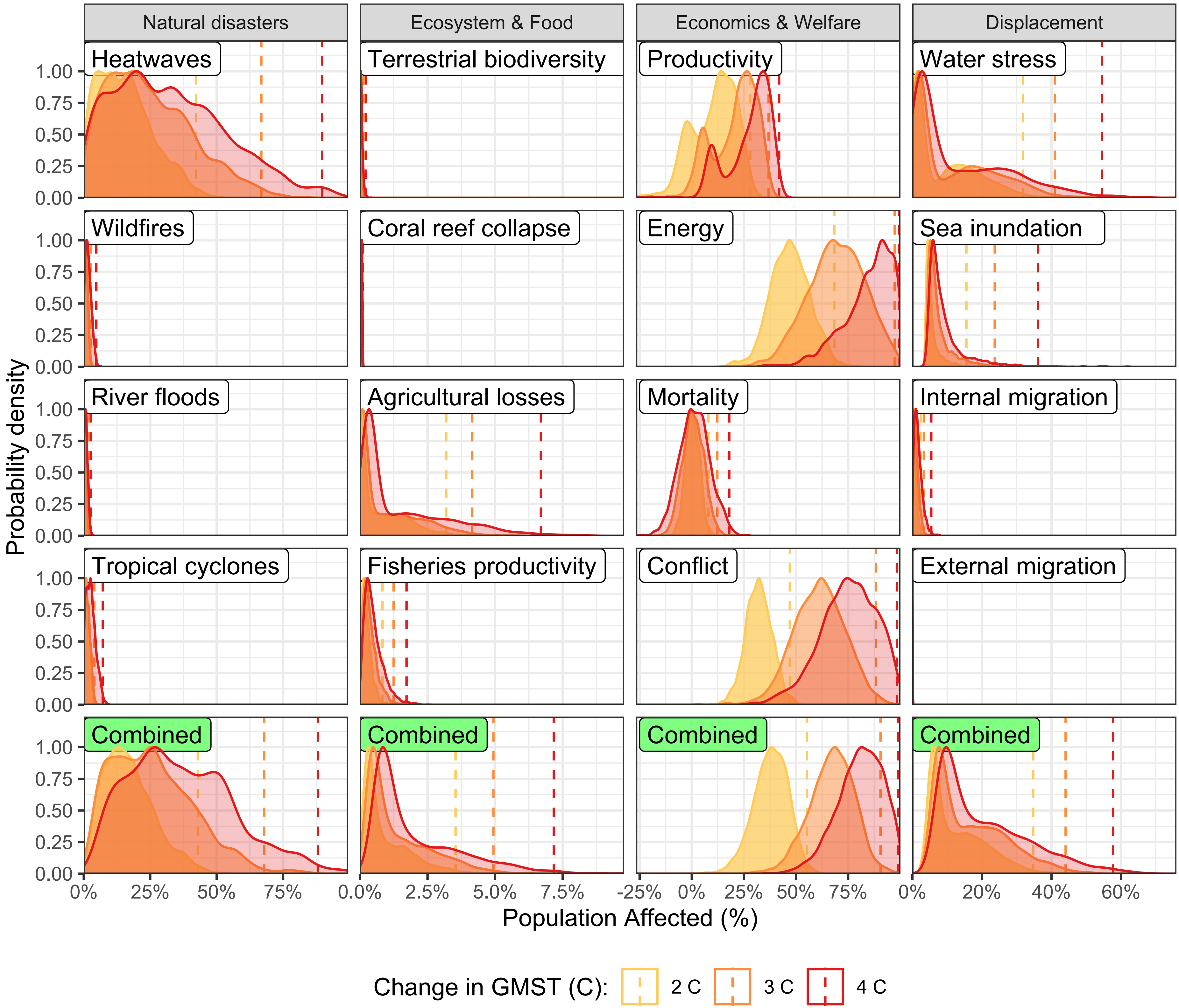

Cascading disasters
Multiple stressors
Cascading social changes
Climate/Environment System
Exposure & Sensitivity
Social/Economic System
Natural disasters
Social outcomes
Cascading tipping points
Simultaneous exposure/sensitivity changes



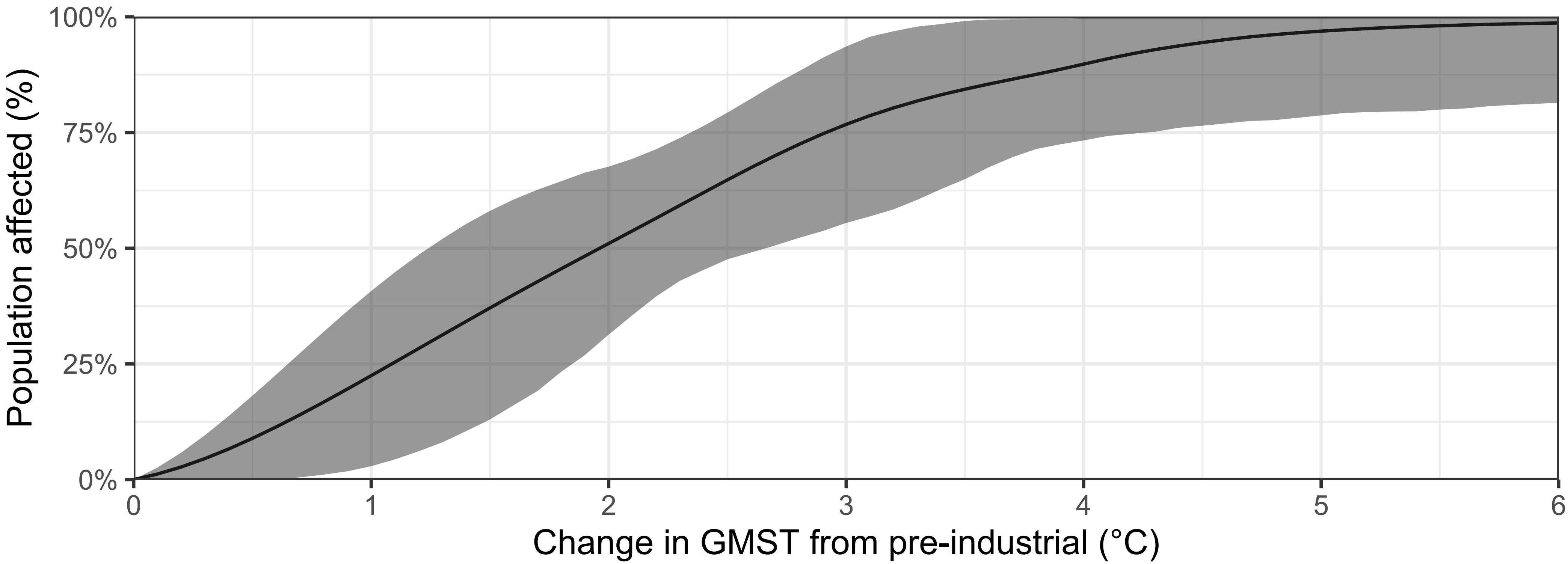
Hazard
Flood
Drought
Precip. Variation
Chill
Heat
Insignificant
Z-Score
0
1
2
3
4
5
50
0
-50
-100
0
100



Flood
Drought
Precip. Variation
Chill
Heat
Population (millions)
750
500
250
0
-4
-2
0
2
4
6
Z-score relative to recent climatology



Natural disasters
Ecosystem & Food
Economics & Welfare
Displacement
Heatwaves
Terrestrial biodiversity
Productivity
Water stress
Wildfires
Coral reef collapse
Energy
Sea inundation
River floods
Agricultural losses
Mortality
Internal migration
Tropical cyclones
Fisheries productivity
Conflict
External migration
Combined
Combined
Combined
Combined
Probability density
0.00
0.25
0.50
0.75
1.00
0%
25%
50%
75%
0.0%
2.5%
5.0%
7.5%
-25%
0%
25%
50%
75%
0%
20%
40%
60%
Population Affected (%)
Change in GMST (C):
2 C
3 C
4 C


Population affected (%)
100%
75%
50%
25%
0%
0
1
2
3
4
5
6
Change in GMST from pre-industrial (°C)